Machine Vision-Based Automatic Raw Fish Handling and Weighing System of Taiwan Tilapia

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Abstract. This study proposes a vision-based automatic raw fish handling system to speed up fish cleaning and weighing. The proposed fish weighing system used a camera to capture projected images of fishes. Applying image processing techniques, physical properties of fishes, such as length, width, perimeter and area were obtained. Followed by regression analysis, weight-length, weight-height, weight-perimeter and weight-area relationships were derived. Analysis results of fifty tilapias show that coefficient of determination of the regression equation relating weight and area is 0.9303. The high value suggests that a tilapia's weight is highly correlated with its projected area. Therefore, use a tilapia's area to estimate its weight is justifiable.

Keywords: Machine Vision, Raw Fish Handling, Fish Weighing, Regression Analysis, Tilapia.

1 Introduction

For some years now, there have been both an increased demand for, and value attributed to higher quality of Taiwan tilapia. Tilapia of the 21st century is a valuable food fish. Typical demands include high economic worth and high protein content; it becomes a major source of animal proteins for human being. In view of that, the food and agriculture organization of the united nation is currently promoting the farming of tilapia intensively. Thus, we can foresee that farmed tilapia will play an important role in food fishes.

Machine vision, an important technique for inspection, measurement, sorting, remote sensing, surveillance, etc., has been extensively used in manufacturing and food industries. In addition, machine vision technique also has been used in agriculture and fishery industries for sizing, counting, weighing, grading, recognition, classification, and monitoring [1-3]. During biology study physical properties, such as length, width, thickness, area, weight, volume, perimeter, compactness and circularity are commonly used as a basis for sizing [4-7], weighing [8-10], grading [11, 13], or classification [14-16]. Martinez presents new low-cost systems for the automation of some fish farm operations. Particularly, computer vision is applied to non-contact fish

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weight estimation. White Trials of a computer vision machine (The Catch Meter) for identifying and measuring different species of fish. Shieh and Petrell adopted stereographic video technique to size salmons. Buckingham used machine vision technique to cut fish head off.

Tilapias are sold by their weights; as a result, it is necessary to develop a quick and accurate weighing method. Currently fish weighting is carried out manually using a weighing scale. Manual weighing is indeed an accurate means, but it is manual and time-consuming. To automate fish weighing, Mathiassen describe a proof-of-concept prototype of an automated system for weight and quality grading of pelagic fish using a multi-modal machine vision system combined with robotized sorting. Omar presents an optimal portion control technique for food processing which is being developed depends on fast on-line measurement of the weight distribution of each incoming food item. Line developed three models to estimate fish mass using truss lengths. Although much work has been done on examining the weight-length relationship of salmons, little attention has been devoted to explore the weight-area relationship. More importantly, tilapia is the most popular fish of cultivating kind in Taiwan. Therefore, the purpose of the study was to investigate the relationship between weight and area of tilapias using regression analysis and then use the derived relationship to establish a quick and accurate vision-based fish weighing system.

2 Materials and Methods

2.1 Fish and Fish Sampling

The experimental samples consisted of 150 tilapias having an overall length of between 25cm to 35cm and a weight of between 300g to 700g. All tilapias were uniform in shape and kindly provided by Guang-Ji fresh market. The samples were randomly divided into two groups. The first group consisted of 50 tilapias was used to explore weight-length, weight-height, weight-perimeter and weight-area relationships. The second group consisted of 110 tilapia was mainly used to verify the relationships established by the first group. Fig. 1 shows an ordinary tilapia sold in fresh market.

Fig. 1. An ordinary tilapia sold in a fresh market

2.2 Hardware and Software

Fig. 2 shows the schematic diagram of the proposed automatic fish handling system. Although the system consists of two major sub-systems: raw fish cleaning system (consists of a input slot ①, a processing platform ②, a output slot ③, a group of fish scaler ④, a group of conveyer belts ⑤, a rotating knife ⑥ Machine structure ⑦, a Cistern ⑧.) and machine vision-based weighing system. The fluorescent illuminator has a back lighting through which the camera can acquire image for measuring the physical properties of the fish. The physical properties used in the study include body-length, height, perimeter, area, weight and relationships among these; however, we will devote our discussion mainly to the research and development of the machine vision-based weighing system. Here, a computer vision algorithm was designed to extract the geometrical features of tilapia.

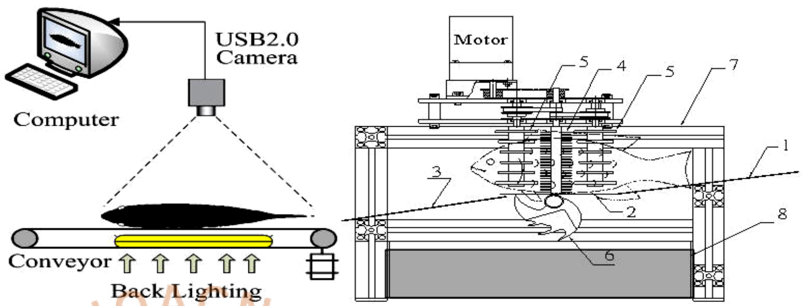


Fig. 2. Schematic diagram of the automatic raw fish handling system

2.3 Raw Fish Cleaning System

The major functions of the raw fish cleaning system include scaling, gutting, and rinsing. Scaling is a process to scrape the scales off the tilapias by using a fish scaler. Gutting is a process to open tilapia's belly using a sharp rotating knife and then pull out its innards (take out viscera). The rinsing process is to wash tilapias, knife, and platform using a large amount of water. As can be seen, the system was controlled by a PLC consisting of a CPU, an input module, and an output module. The input module is responsible for monitoring the signals from proximity sensors, optical sensors, or limit switches. The output module is responsible for turning on the conveyor, fish scaler, rotating knife and drain valves.

At the beginning, a raw fish is manually put into the sliding slot. Then the fish slides into the processing platform by its own weight. Immediately after optical sensor detects the presence of the fish, the system starts automatically. During its transportation by means of a conveyor, the fish is scaled off by a descale mechanism. After that, the fish is further transported by a set of transportation wheels. While the fish is transporting, a rotating knife cuts a slit from its anal opening to the gill openings and the viscera are pulled out. As the fish moves on, another optical sensor is triggered and a water spraying system is actuated subsequently to flush the knife and the platform. Finally, the fish slides down through the output slot to the vision-based weighing system. While the fish is sliding, it is thoroughly flushed by another water spraying system; Fig. 3 shows the processing flow of the automatic raw fish handling system.

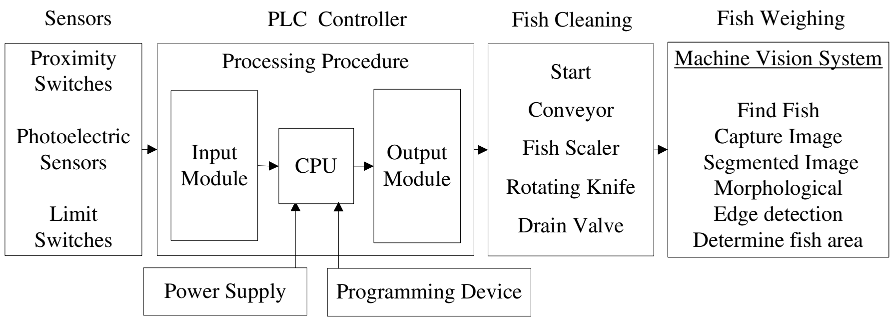


Fig. 3. Processing flow of the raw fish handling system

2.4 Vision-Based Weighing System

Referring to Fig.2, the vision-based weighing system was installed right after the raw fish cleaning system. The machine vision system consists of a CMOS camera, a lens, a fluorescent ring light, and a light controller. The 1280×1024 USB2.0 color CMOS camera from ARTRAY Japan was used to capture tilapias' grayscale image of size 512×480. The FCL-30D fluorescent ring light was used for illumination. The ring light has a diameter of 29 mm and provides a maximum lumen of 1400 Lm. The color temperature is 6200K. The light controller was used to adjust the intensity of the ring light. In the research, a USAF glass slide resolution target from Edmund Optics was used in calibration to derive the scale factor (μm/pixel, mm/pixel, cm/pixel, etc) of the vision system. The functioning of a general machine vision-based weighing system can subdivide into several steps, as presented in Fig 4.

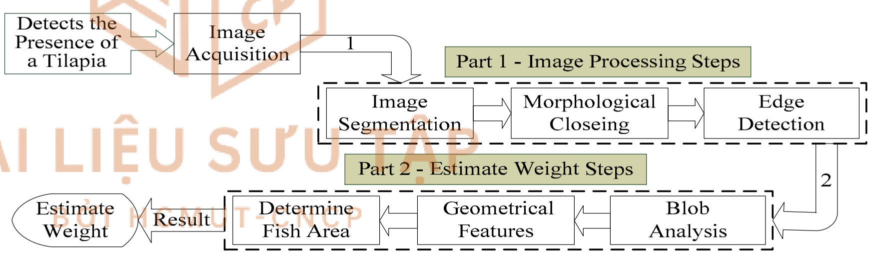


Fig. 4. Model of a typical machine vision-based weighing system: part 1 - image processing steps; part 2 - estimate weight steps

2.5 Experimental Method

The experiment is carried out in three phases: In the first phase, the tilapias in both groups were measured manually to obtain their weights, lengths, heights, perimeters and areas. Then data from the first group were analyzed using linear regression techniques to build the relationships between weight and physical properties. The objective of the first phase is to see which relationship is better correlated. In the second phase, we used the vision-based weighing system to obtain the weights of the tilapias in the first group. More specifically, we applied machine vision techniques to acquire the physical properties of each tilapia in the first group and used these data to estimate fish weights. Finally, the weights obtained by the two methods were compared to reveal the performance of the vision-based weighing system.

Acquire Physical Properties of Tilapias. The physical properties used in the study include length, height, perimeter, area and weight. Both width and height were measured using a vernier caliper. In the study, we used a weighing scale to obtain a tilapia's weight. A fish's area and perimeter was placed on a regular graph paper and its profile was drawn. Then the fish's area was obtained by accumulating the area enclosed by the profile of the fish. Here, we defined the length of a tilapia as the horizontal distance between the tip of its mouth and the farthest point on the caudal fin. The height of a tilapia is defined as the vertical distance between the highest point of the dorsal fin and lowest point of the ventral fin. Table 1 shows only the areas and the weights of the 50 tilapias in the first group.

Table 1. Manually measured weights (W) and areas (A) of the 50 tilapias in the first group

No.	W(g)	A(cm^2)	No.	W(g)	A(cm^2)	No.	W(g)	A(cm^2)	No.	W(g)	A(cm^2)
1	388	230.30	14	570	274.25	27	490	242.90	40	638	296.00
2	428	234.06	15	492	253.58	28	480	252.60	41	602	273.70
3	352	220.60	16	496	244.89	29	512	255.20	42	600	266.00
4	374	227.70	17	462	248.10	30	460	233.91	43	616	273.30
5	450	251.07	18	436	237.16	31	484	248.40	44	584	285.30
6	462	245.40	19	432	231.26	32	528	254.20	45	482	251.35
7	332	214.10	20	464	250.66	33	498	2420	46	454	240.08
8	338	208.20	21	418	235.76	34	442	239.9	47	484	242.99
9	444	238.35	22	442	234.70	35	610	292.10	48	484	246.30
10	388	231.8	23	408	224.60	36	746	309.80	49	440	230.10
11	408	216.77	24	428	232.06	37	678	296.20	50	388	224.29
12	388	231.08	25	558	270.70	38	574	265.95			
13	360	214.10	26	512	268.30	39	684	308.10			

Establish Regression Models. Once required data are carefully measured, the next step is to use data of the first group to establish the relationships between weight physical properties. In the study, we assumed that there are linear relationships between weight and length, height, perimeters and area. The relationships are governed by the following equation:

$$y = mx + b \tag{1}$$

where x represents the length, the height, the perimeter or the area of a tilapia; y denotes the weight of the tilapia; m and b are the slope and the y-intercept of the best-fit straight line, respectively.

(a) The Relationship between Weight and Length. The relationship between weight and length can be derived by using a scatter diagram. It can be seen from Fig. 5 that there exists a positive correlation between tilapia weight (*W*) and tilapia length (*L*). Through regression analysis, we can identify the exact relationship. As we assume that the relationship between weight and length is linear, the best-fit linear regression equation is shown in Eq. (2). It is clear that a tilapia's weight increases with its overall length. The symbol R^2 is Coefficient of Determination (abbreviated as CoD). Actually, the value of CoD provides us a measure of the strength of the linear relationship between weight and length of tilapias.

$$W = 59.056 * L - 1305.3 \tag{2}$$

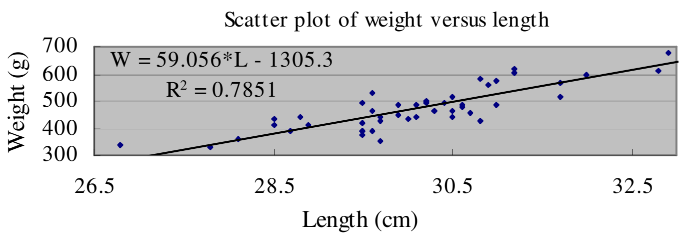


Fig. 5. The linear relationship between the weight (W) and the length (L) of tilapias

(b) The Relationship between Weight and Height. Similarly from the linear regression analysis results of the data collected from the first group, we found that there is a positive correlation between the weight (W) and height (H) of a tilapia. Fig. 6 shows the scatter plot of the 40 tilapia and the derived linear regression line. The linear regression equation relating weight and height is shown in Eq. (3). The R^2 value is 0.791. As you can see from the plot, a tilapia's weight also increases linearly with its height.

$$W = 86.995 * H - 538.26 \tag{3}$$

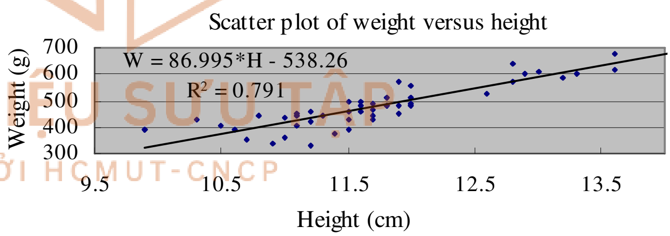


Fig. 6. The linear relationship between the weight (W) and the height (H) of tilapias

(c) The Relationship between Weight and Perimeter. The relationship between weight and perimeter can be derived by using a scatter diagram. It can be seen from Fig. 7 that there exists a positive correlation between tilapia weight (*W*) and tilapia perimeter (*P*). Through regression analysis, we can identify the exact relationship. As we assume that the relationship between weight and perimeter is linear, the best-fit linear regression equation is shown in Eq. (4). The R^2 value is 0.8216.

$$W = 21.663 * P - 1351.4 \tag{4}$$

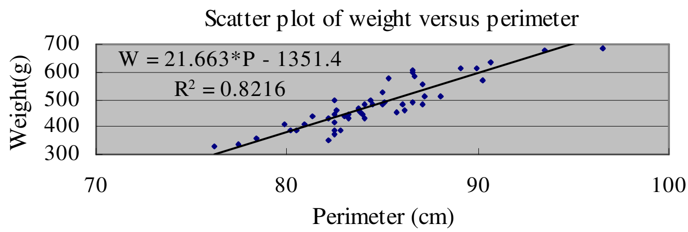


Fig. 7. The linear relationship between the weight (W) and the perimeter (P) of tilapias

(d) The Relationship between Weight and Area. Based on the linear regression analysis result, we found that there is a positive correlation between the weight (*W*) and the area (*A*) of a tilapia. Fig. 8 shows the plot of tilapia weight versus tilapia area. The linear regression equation relating weight and area is shown in Eq. (5).

$$W = 3.7074 * A + 438.66 \tag{5}$$

It is evident that the weight of a tilapia increases with its area. The R^2 value is 0.9722 indicating that 97.22% of the variation in the weight of a tilapia may be explained by its area. Since CoD is very close to one, it indicates that an excellent linear reliability exists between the weight and the area of a tilapia.

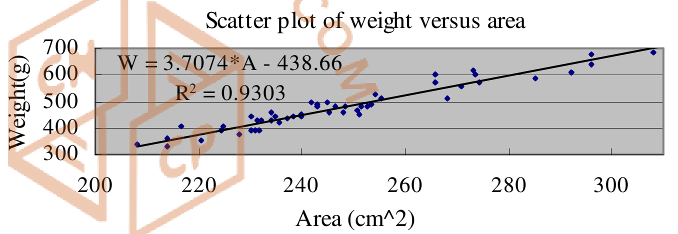


Fig. 8. The linear relationship between the weight (W) and the area (A) of tilapias

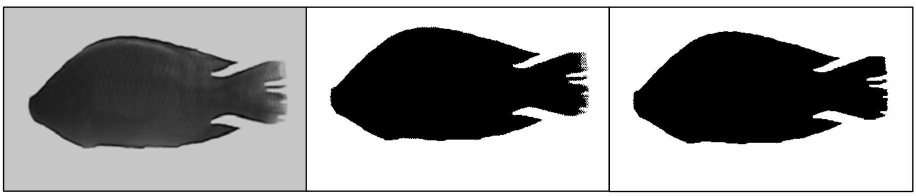
(e) Choose a Regression Model for Weighing Tilapias. From the results as shown in Figs. (5) - (8), we found that a tilapia's weight is linear correlated with its length, height, perimeter and area. However, a tilapia's area has a greater influence on its weight. In other words, a tilapia's weight is more closely related to its area than its perimeter, length or height. As a result, we decided to use the relation between weight and area to weigh tilapias. In summary, a tilapia's weight was estimated by plugging the area acquired by the machine vision-based weighing system into Eq. (5). Of course, a tilapia's area will be determined by image processing techniques that will be described in detail in the following section.

3 Results and Discussions

3.1 Weigh by Machine Vision

The object of the current step is to collect area of the individual tilapias in the second group. Once each tilapia's projected area has been obtained using the vision-based weighing system, we then made use of the regression equation as shown in Eq.(5) to evaluate its weight. For ease of understanding, the processing flow is divided into the following four steps:

(1) Segment the fish image as shown in Fig. 9a using Otsu's thresholding method to obtain the resulting binary image shown in Fig. 9b.
(2) Apply morphological closing operation to the binary image to fill small holes and smooth the profile of the fish. Fig. 9c shows the resulting image.
(3) Determine fish area using blob analysis technique.
(4) Plugging a tilapia's area into Eq. (5) to determine its estimated weight.



(a) (b) (c)

Fig. 9. Image processing steps for the weighing of raw fishes: (a) grabbed image of a tilapia using a backlighting illumination; (b) Segmented image using Otsu's thresholding method; (c) Resulting fish image after morphological closing operation

3.2 Comparison Results and Weighing Error Analysis

The system is capable of processing 15 to 20 tilapias per minute. To verify the accuracy of the vision-based weighing system, the weighing results of the second group derived in Sections Acquire Physical Properties of Tilapias and Weigh by machine vision respectively were compared. Table 2 shows a partial list of the comparison results, where A is the area determined by vision system, W_1 is the weight obtained manually using a weigh scale, W_2 is the weight evaluated by the regression equation shown in Eq. (5), and ε is the difference between the regressed fish weight and the actual fish weight. For simplicity, let W_1 be the actual fish weight; W_2 be the regressed fish weight; and ε be the weighing error. Thus $\varepsilon = W_1 - W_2$.

As can be seen from Table 2, the maximum weighing error, mean weighing error, and standard deviation of the weighing error are 9.12g, 1.77g, and 2.21g, respectively. Moreover, the percentage of the maximum error and mean error of the weighing is 1.97% and 0.83%, respectively. It is worth mentioning that the low weighting errors indicate that we can estimate a tilapia's weight by its area with a maximum error of 1.97% of its actual weight.

Table 2. Area (A), actual weight (W_1), regression weight (W_2) of tilapias in the data set

No.	A (cm^2)	W_1(g)	W_2(g)	ε (g)	ε %	No.	A (cm^2)	W_1(g)	W_2(g)	ε (g)	ε %
1	238.18	442	444.35	-2.35	0.53	26	229.86	408	413.52	-5.52	1.35
2	228.93	408	410.06	-2.06	0.50	27	223.53	388	390.04	-2.04	0.53
3	232.81	428	424.46	3.54	0.83	28	213.97	360	354.62	5.38	1.49
4	268.24	558	555.82	2.18	0.39	29	223.66	388	390.52	-2.52	0.65
5	256.07	512	510.70	1.30	0.25	30	233.38	428	426.57	1.43	0.33
6	244.83	462	469.02	-7.02	1.52	31	214.35	352	356.02	-4.02	1.14
7	208.04	332	332.62	-0.62	0.19	32	271.03	570	566.15	3.85	0.68
8	209.42	338	337.75	0.25	0.07	33	250.95	492	491.72	0.28	0.06
9	237.50	444	441.84	2.16	0.49	34	302.08	678	681.26	-3.26	0.48
10	223.90	388	391.42	-3.42	0.88	35	272.21	574	570.52	3.48	0.61
11	251.62	490	494.21	-4.21	0.86	36	219.83	374	376.33	-2.33	0.62
12	248.92	480	484.19	-4.19	0.87	37	248.18	484	481.46	2.54	0.52
13	254.25	512	503.96	8.04	1.57	38	236.43	440	437.89	2.11	0.48
14	275.26	584	581.84	2.16	0.37	39	222.62	388	386.67	1.33	0.34
15	248.89	482	484.07	-2.07	0.43	40	245.94	464	473.12	-9.12	1.97
16	242.18	454	459.19	-5.19	1.14	41	233.04	418	425.33	-7.33	1.75
17	250.58	484	490.35	-6.35	1.31	42	240.95	460	454.65	5.35	1.16
18	254.09	498	503.35	-5.35	1.07	43	247.60	484	479.28	4.72	0.98
19	236.20	442	437.04	4.96	1.12	44	262.96	528	536.24	-8.24	1.56
20	284.78	610	617.12	-7.12	1.17	45	279.96	602	599.27	2.73	0.45
21	320.09	746	748.06	-2.06	0.28	46	281.14	600	603.65	-3.65	0.61
22	254.47	496	504.77	-8.77	1.77	47	285.70	616	620.53	-4.53	0.74
23	241.99	462	458.48	3.52	0.76	48	304.12	684	688.83	-4.83	0.71
24	236.70	436	438.89	-2.89	0.66	49	289.38	638	634.19	3.81	0.60
25	233.59	432	427.35	4.65	1.08	50	238.07	450	443.95	6.05	1.34

4 Conclusions

This paper has presented a new method and an apparatus for automatically cleaning and weighing of tilapias. On the basis of the regression analysis results, we discovered that a tilapia's weight is highly correlated with its projected area. Thus, it is reasonable to use a tilapia's projected area to estimate its weight. The research results might help fish provider, especially fresh marketer, reducing the highly labor intensity of fish cleaning and weighing. Currently a fish weight is derived using only its area without considering its thickness. In the future, we will incorporate thickness into analysis. Hopefully, the weighing accuracy can be increased.

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